THE IMPACT OF RAINFALL VARIABILITY ON AGRICULTURAL PRODUCTION AND HOUSEHOLD WELFARE IN RURAL MALAWI

BY

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THESIS

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Abstract

This thesis uses Malawi's Third Integrated Household Survey 2010 – 2011 combined with improved rainfall estimates from a 30-year time series to create an objectively measured drought index. I first estimate the impact of this severe negative rainfall shock, defined as precipitation levels during the reference season of interest more than twenty percent less than the long-run median, on numerous indicators of agricultural production and household welfare. I then examine the extent to which households are able to mitigate the impact of a negative rainfall shock through a variety of plot and household-level characteristics. Findings reveal that households experiencing a severe negative rainfall shock during the wettest quarter of the 2008/2009 or 2009/2010 agricultural seasons, on average, suffered from significantly lower maize yields, values of agricultural output, total per capita consumption expenditures, food expenditures and dietary diversity. Households that planted tobacco as the primary crop, were located in a tropic-cool/semiarid agroecological zone or had access to credit appeared better able to protect their agricultural production and consumption levels from the negative impact of the rainfall shortage.

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Chapter 1

Introduction

It is clear that climate change is an inevitable phenomenon. As developing countries are highly dependent on agriculture, there are ever growing concerns that this change in weather variability will further threaten the welfare and food security of already highly vulnerable rural households in developing nations and pose a serious challenge to development efforts. In light of this impending threat, it is imperative that we have a deeper understanding of the impact of weather extremes on the poor and the effectiveness of current coping mechanisms.

Although shifts in rainfall and weather patterns are occurring worldwide, Barrios et al (2008) found that agricultural production in Sub-Saharan Africa is, relative to other developing countries, particularly sensitive to weather variability as the availability of water differs widely throughout the geographically diverse continent. Though this thesis will focus on a short-term weather shock, understanding the impact of weather extremes on production and welfare in a particular season is made more pressing by global climate change, as it is likely to increase the frequency and severity of weather variability.

The primary objective of this thesis is to model the effects on agricultural production and household welfare of an objectively-measured, severe rain shortfall in a drought-prone region of Sub-Saharan Africa, namely Malawi, where the population is predominantly rural, relying almost exclusively on rainfed agriculture. The secondary objective is to identify plot and household characteristics that serve to mitigate or exacerbate the effects of experiencing a negative rainfall shock.

Using data collected in Malawi's Third Integrated Household Survey in 2010 – 2011 (IHS3) combined with rainfall estimates from the past 30 years, I first quantify severe negative rainfall shocks for the agricultural seasons reported in the survey. I then take advantage of the detailed agriculture, household and community modules included in the IHS3 survey on agriculture to measure the extent and pathways through which households are impacted by this lack of rain.

I carry out the following analyses. Prior to estimating the impact of a negative rainfall shock on several measures of household welfare, I present results from a production function to illustrate the negative effect of rainfall shortages on maize yields and the value of agricultural output. Then, to measure the response of households to weather variability, I first examine the effect of experiencing a negative rainfall shock on per capita consumption expenditures while controlling for socioeconomic characteristics, interacting this weather shock with key household characteristics to determine the factors that make household consumption more resistant or vulnerable to rainfall shocks. I also examine the effect of rainfall shocks on different components of household expenditures, such as food and non-food items, to determine the expenditures that households prioritize when dealing with an agricultural income shock.

Although a number of papers have studied the impact of weather shocks on households, this thesis is unique and adds to the literature in a number of ways. First, for each plot that informs the analysis, I rely on an objective measure of a seasonal severe rain shortfall with respect to a plot-location-specific long-term trend during a plot-location-specific reference period that is deemed critical for agricultural production. This is the first study that relies on geo-referenced plot locations for the study of the effects of negative rainfall shocks on agricultural production, and the geospatial rainfall data is available in a fairly disaggregated manner, at a resolution of approximately 5x5 kilometers. The alternative is to rely on subjective reports of drought experienced by households in a reference period that is dependent on the interview date of the household. Shortcomings of this method are recognized in section 2.2.3. Second, this is the first comprehensive study of the effects of severe rain shortfalls on agricultural production and household welfare in Malawi that is able to match objective measures of rainfall data with information on agricultural plots and households recovered as part of a nationally representative multi-topic household survey. The previous studies in the Malawian context have relied on subjective drought reports of sample households to estimate similar effects. Third, the objective measures of rainfall for each 5x5 km pixel that contains plot locations are derived based on a 30-year complete weather station time series and an innovative technique developed by the United States Geological Survey as part of the Famine Early Warning Systems Network (FEWSNET) monitoring program that is designed to yield improved rainfall estimates with respect to publicly-available global rainfall data that are defined at a 8x8 km resolution.

The rest of this thesis will be organized as follows. Chapter 2 presents a discussion of previous research examining the effect of weather variability on agricultural production and household welfare and provides background information on Malawi's agricultural sector and climate. Chapter 3 describes the dataset used for this analysis along with the methodology, focusing on the estimation of the impact of rainfall variability on household expenditure per capita, caloric intake and food diversity. Chapter 4 presents the estimation strategy, Chapter 5 shares the results and Chapter 6 concludes.

Chapter 2

Previous Research and Background

This Chapter provides an overview of the literature related to this thesis and background information on Malawi. Starting with a broad look at the relationship between climate change, weather variability and agriculture, I will then detail previous work that has been done studying the links between shocks and household welfare.

2.1 Climate Change vs. Weather Variability

2.1.1 Climate Change

It is becoming ever more apparent in the scientific literature that higher temperatures and changing precipitation levels due to climate change will depress crop yields in many countries throughout the coming decades (Yesuf et al 2008). According to projections by the Intergovernmental Panel on Climate Change (IPCC), rainfall variability and extreme climatic events such as droughts are expected to adversely affect agricultural production and food security (Christiansen et al 2007), with Boko et al (2007) predicting that yields from Africa's rainfed farm production could decrease 50% by the year 2020 as a result.

2.1.2 Weather Variability

Though country-level studies using simulation techniques have added a great deal to the literature on climate change, for the purposes of this thesis it is important to distinguish between climate change, climate variability and weather variability. Whereas "weather refers to the atmosphere's evolution over short periods of time, climate is the expected distribution of weather; therefore climate change refers to the statistical distribution of weather occurring over decades and centuries" (Auffhammer et al 2011). Given the long-term nature of climate change, it can often be more easily understood by focusing on short-term weather variability. This thesis focuses on short-term weather variability through the study of one agricultural season per household and the ability of the households to cope with the occurrence of an unexpected negative rainfall shock. The studies discussed throughout the remainder of the paper only refer to those that have used a short-term weather event to construct a measure of a natural disaster.

2.2 Shocks and Household Welfare

The main focus of this thesis is related to a body of literature that studies how shocks impact household welfare and household vulnerability. The level and variability of rainfall are important determinants of persistent food insecurity and household vulnerability (Demeke, Keil and Zeller 2011).

2.2.1 Covariate vs. Idiosyncratic Shocks

Many papers have considered the impact of both covariate and idiosyncratic shocks on households. Whereas idiosyncratic shocks are household specific and allow those affected to rely on relatives and neighbors, covariate shocks affect the entire community, thus preventing assistance from social networks. Several studies have attempted to estimate the relative importance of covariate and idiosyncratic shocks on household consumption with their results indicating that covariate shocks have a more significant impact on consumption expenditures than idiosyncratic shocks (Dercon and Krishnan 2000; Harrower and Hoddinott 2008). The magnitude of the shocks, however, plays an important role.

2.2.2 Weather Shocks and Household Consumption

The impact of covariate weather shocks on household consumption in rural areas stems from the loss of agricultural income resulting from a decrease in crop yields. A reduction in agricultural income may then translate into a decrease in consumption (Jacoby and Skoufias 1998). The extent to which a household's consumption expenditures are reduced by this loss of income is highly dependent on the ability of the household to cope after being exposed to the shock.

Many studies have examined the impacts of weather-related shocks on dimensions of welfare; overall their findings indicate that "agricultural incomes and, thus, food, basic non-food consumption and investments in human capital, health, nutrition and productive physical assets, are likely to be negatively affected by extreme weather events". (Skoufias, Rabassa, and Olivieri 2011)

Studies have also shown that when consumption is affected by a shock, different categories of consumption may be impacted differently. Skoufias and Quisumbing (2005) show that, in general, food consumption is better insured than non-food consumption. Duflo and Udry (2004) provide a further breakdown of this concept and show that the gender of the agricultural income earner impacted by the shock can influence the type of consumption affected as husbands and wives typically farm separate plots and specialize in the growth of certain crops. Shocks that increase the production of crops predominantly cultivated by women shift expenditures toward non-staple foods, whereas similar shocks impacting crops cultivated by men seem to have no effect on the purchases of food.

2.2.2.1 Malawian Context

Studies that have focused on the impact of shocks in Malawi, in particular, have documented the negative effect on different measures of welfare; however, to my knowledge, none have developed a drought index similar to that used in this paper. Davies (2010) studied two household shocks (sickness and death) and two community shocks (floods and negative rainfall shocks) and found that negative rainfall shocks have negative short-term effects on consumption levels, but do not have significant long-run effects. Devereux (2007) adapted Sen's entitlement approach to the analysis of the impacts of droughts and floods in the context of Malawi's food crises in 2005/2006. He characterizes these impacts as a sequence of interacting "entitlement failures" where weather shocks first disrupt production, then labor and commodity markets, so that labor and trade-based entitlements to food are undermined. Emphasizing the importance of public intervention and mitigation strategies, he finds strengthening production systems by introducing irrigation to reduce dependence on unreliable rainfall to be the best household-level solution to prevent subsistence crises.

2.2.3 Studies using Weather Data

The studies mentioned thus far have used subjective measures of shocks typically generated from responses to questions included in shock modules used in household questionnaires. Though this method is certainly useful, it may not provide an accurate representation of those respondents that have experienced a negative rainfall shock - many factors can influence a household's likelihood of reporting that they experienced a shock. Traerup and Mertz (2010) examined the potential relationships between rainfall data and household self-reported harvest shock and although they found that shocks reported by households appear to correspond well with observed variability in rainfall patterns, other studies emphasize possible endogeneity issues. The methodological shortcomings of subjectively reported shocks stem from the motivation behind a household reporting said shock. Whether or not a household considers a shortage of rainfall in a particular season to be a drought depends on their ability to cope with the shock. If a household already has coping strategies in place prior to a drought, then studies using a subjective measure would underestimate the full welfare cost of the shock.

Few studies use actual weather data to analyze the relationship between weather and the level of household welfare; however those that do provide the basis for the methods that will be used in this thesis. Recent papers that have used similar methodology develop drought indices or some other objective measure of a covariate weather shock, and then use this definition to study the effect on some measure of household welfare.

Skoufias, Vinha and Conroy (2011) study the impact of climate variability on welfare in rural Mexico by defining weather shocks as rainfall or growing degree days more than one standard deviation from their respective long-run means. They use these definitions to examine the impact on household consumption per capita and child height-for-age and find that current risk-coping mechanisms, such as participation in supplemental nutrition programs, are not effective in protecting these dimensions of welfare from erratic weather patterns.

Skoufias, Essama-Nssah and Katayama (2011) build on these insights and study the impact of weather shocks on household welfare in rural Indonesia, though they define weather shocks slightly differently. In particular, they consider two shocks: a delay in the onset of monsoon, and a significant shortfall in the amount of rain in the 90-day post-onset period. They find that the monsoon delay does not have a significant impact on the welfare of rice farmers, but households exposed to low rainfall are negatively affected, though able to protect their food expenditures at the expense of lower nonfood expenditures. Then, using propensity score matching, the authors identify community programs that might moderate the welfare impact of this type of shock and find that access to credit and public works projects have the strongest moderating effects.

Thomas, Christiaensen, Do and Trung (2010) estimate the welfare effects associated with natural disasters through the creation of natural disaster and hazard maps from first hand, geo-referenced meteorological data in Vietnam. Using repeated cross-sectional national living standard measurement surveys from 2002, 2004, and 2006, the authors estimate the welfare effects of several natural disasters by augmenting reduced form consumption equations with the disaster measures derived from the hazard maps. The group of natural disasters studied included drought events, measured as 20 percent or more below the median rainfall for the period from 1975 – 2006. The results suggest that households in Vietnam generally manage to cope with the immediate effects of droughts, largely through irrigation but also through income diversification and self-insurance through asset disposal. However, there are important long-run negative effects from these shortages in rainfall. The frequent occurrence of droughts erodes the ability of households to cope over time, resulting in a substantial welfare loss - households in areas with a 10 percentage point higher frequency of drought are on average 12 percent poorer households in drought prone areas, especially those closer to urban centers (areas with more than 500,000 inhabitants). Households in drought prone areas further away from urban centers also experience losses, however disaster relief efforts tend to be focused on areas greater than 2 hours away from metropolitan areas so these localities are better able to maintain their asset bases.

This thesis will build further upon these insights - first examining the effect of a drought on welfare outcomes similar to those previously mentioned, such as consumption expenditure shares, but also estimating the impact of a drought on a measure of dietary diversity. Then I examine the effectiveness of coping mechanisms that households have in place.

Despite the plethora of literature that exists on the impact of rainfall shocks on different measures of wellbeing, there remains a pressing need for further study in this area as households are still negatively affected by unexpected rainfall patterns. As noted in Chapter 1, this thesis contributes to the literature through an in-depth look at objectively measured rainfall shocks during the 2008/09 and 2009/10 agricultural seasons in rural Malawi using the most recent nationally representative data available.

2.3 Background

This section provides a brief overview of Malawi's economy, agricultural sector, agricultural season, climate and the impact that the interaction of these factors has had on food security.

2.3.1 Malawi

Malawi is a small, landlocked country located in southeast Africa and is considered among the world's least developed countries. It is a severely poor country facing chronic malnutrition, extreme income inequality, high population density, and shortages of land (Actionaid 2006).

2.3.2 Malawi's Agricultural Sector

Malawi is a predominantly rural country with the majority of its households at least partially dependent on agriculture for their livelihood. The agricultural sector composes 36% of Malawi's GDP and represents about 80% of all exports with tobacco, tea, and sugar as its most important export crops. Close to 90% of the population engages in subsistence farming, and smallholder farmers produce a variety of crops, including maize, beans, rice, cassava, tobacco and groundnuts. Agriculture contributes about 63.7% of total income for the rural population and 87% of total employment, making the population particularly vulnerable to external shocks such as drought.

2.3.3 Agricultural Season

Agriculture in Malawi is characterized by a rainy and a dry season. The dry season generally runs from April to September with the main harvest occurring during this time period. The rainy season generally starts mid-October and lasts through March. The main harvest planting begins just before the rainy season starts and lasts from the beginning of October to mid-January. Labor demand peaks during the planting season. An outline of the seasonal calendar and critical events relating to maize production and its effect on labor and food security can be found in Figure (1). The timing of these events plays an important role in the development of the drought index used later in this paper.

2.3.4 Weather Variability in Malawi

Malawi provides a very relevant setting to study the impact of rainfall variability on household welfare as the weather is highly variable. Malawi has suffered four major droughts over the last twenty years and experiences ongoing struggles with erratic rains. The impact of rainfall variability and droughts can be devastating to the people of Malawi. The most recent major drought occurred during January and February of the 2005 agricultural season and caused a 30 percent drop in the maize harvest from the previous year, resulting in the worst season in 10 years and a severe food crisis. The agricultural seasons of interest in this thesis experienced rainfall shortages that were not as detrimental to the population as a whole; however, as observed by project managers and enumerators conducting Malawi's Third Integrated Household survey, households throughout different regions of Malawi that did not receive adequate rain suffered a great deal. Not only does Malawi need to be better prepared for the possibility of major droughts in the future, but they need to develop the resources to deal with yearly fluctuations in rainfall as the country continues to suffer from food crises caused by these erratic rains and regular floods.

Chapter 3

Data and Methodology

To study the impact of negative rainfall shocks on measures of agricultural production and household welfare, I use a multi-topic nationally representative household survey conducted in Malawi along with dekadal (period of ten days) rainfall data covering a 30-year period. The combined data set provides the necessary details on rainfall, and plot and household characteristics, to properly conduct my analysis. This chapter provides an overview of Malawi's Third Integrated Household Survey dataset used to examine the impact of negative rainfall shocks on maize yields, the value of agricultural output, household consumption expenditures and food intake, as well as information on how the rainfall estimates were obtained. It will then detail the process used to create the drought index and finally, describe the methods used to create the model outlined in the next chapter.

3.1 Malawi Third Integrated Household Survey 2010 - 2011

The data used for this thesis comes from household-level and plot-level data from Malawi's Third Integrated Household Survey (IHS3) complemented by rainfall data covering the period from 1981 to 2010. The IHS3 Survey was conducted from March 2010 to March 2011 by the Malawi National Statistical Office, with support from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project.[1] The IHS3 data

[1] The LSMS-ISA initiative is a household survey program established by a grant from the Bill and Melinda Gates Foundation to provide financial and technical support to governments in sub-Saharan Africa in the design and implementation of nationally-representative multi-topic panel household surveys with a strong focus on agriculture (www.worldbank.org/lsms-isa). The IHS3 data and documentation are publicly available through the LSMS-ISA website.

were collected within a two-stage cluster sampling design, and are representative at the national-, urban/rural-, regional-, and district-levels. The sample covers the three main regions of Malawi, namely North, Central and South. The total sample consists of 12, 271 households drawn from 728 census enumeration areas (EAs) including 31 districts, of which 27 were considered rural. Although the data are not longitudinal, the survey provides a rich set of variables through Household, Agriculture, Fishery, and Community Questionnaire survey instruments.

For both the agricultural production and household welfare analyses I use information collected in the mulit-topic Household Questionnaire administered to all sample households. The instrument collected (i) individual-disaggregated information on demographics, education, health, wage employment, anthropometrics, and control of income from non-farm income sources, and (ii) data on housing, food consumption, food and non-food expenditures, food security, nonfarm enterprises, and durable and agricultural asset ownership, among other topics. Additionally, each household was georeferenced using a handheld Global Positioning System (GPS) unit. Of the 12, 271 households surveyed, 10,104 were involved in agriculture and 9, 473 of these households were located in rural areas.

Additionally, a Community Questionnaire was administered in each IHS3 EA to a focus group composed of 5 to 15 knowledgeable residents of the community, including the village headman, school headmaster, agricultural field assistant, health workers, religious leaders, local merchants and other long-term residents. The instrument gathered information on a range of community characteristics, including religious and ethnic background, physical infrastructure, access to public services, economic activities, communal resource management, organization and governance, investment projects, and local retail price information for essential goods and services.

In conducting the analysis on agricultural production, I use the sample of households that were involved in agricultural activities. The households that reported land ownership and/or cultivation of land and/or ownership of livestock were administered the Agriculture Questionnaire. At the plot-level, separately for reference rainy and dry seasons, the questionnaire solicited information on land areas, physical characteristics, labor and non-labor input use, cultivation, and production. The instrument identified household members that managed, owned and/or worked on each plot, and collected GPS-based locations and land areas of the plots reported to have been owned and/or cultivated. The questionnaire also included rainy and dry season specific modules on farm input subsidy program participation, non-labor input purchases, and crop sales and disposition. 10,104 households interviewed owned or cultivated land with this sample containing information on a total of 18,990 plots. The majority of the households surveyed reported information for only one plot, with only 30% of households involved in agriculture having more than one plot.

3.2 Rainfall Data

As mentioned, both the household and plot locations from the IHS3 survey were geo-referenced using a handheld GPS unit allowing us to combine this with weather data and construct precise rainfall estimates for each location.[2] The rainfall data available was collected from 23 weather stations across Malawi and provided estimates for a 30-year period (1981-2010). The objective was to produce rainfall estimates for survey households as long-term averages and seasonal totals for the survey crop year.

[2] To preserve the confidentiality of sample households and communities, the IHS3 applies a random offset within a specified range to the average EA values and provides the off-set EA latitudes and longitudes for public use. For urban areas a range of 0-2 km is used. In rural areas, where communities are more dispersed and risk of disclosure may be higher, a range of 0-5 km offset is used.

Many interpolation methods can be used to produce reliable estimates, but they are limited by the density and distribution of stations. Often economic literature simply matches each locality to the geographically closest weather station; however this may lead to biased estimates if considerable differences exist in terms of topographic characteristics between the locality of the cluster and the location of the nearest station (Rabassa and Skoufias 2012). An alternative approach was developed by researchers at the United States Geological Survey (USGS) to generate improved rainfall estimates (IRE) as part of the Famine Early Warning Systems Network (FEWSNET) monitoring program. This method combines point data with spatially continuous grid data and allows for better estimates of precipitation levels. Essentially, the IRE is produced by interpolating ratios between the point and the grid where these two data are collocated, then multiplying the ratio by the grid.

The LSMS-ISA team relied upon the dekadal FEWSNET climatology. This method captures the historical spatial variability of rainfall by combining monthly mean rainfall measured at stations, slope and elevation parameters, and satellite estimates of precipitation. Building on statistical blending procedures (Funk et al 2007, Funk and Michaelsen 2004), this approach uses a moving window regression to fit local models describing the spatial variations of the mean fields. The FEWSNET climatology depicts average monthly rainfall at 0.05° (approximately 5 km) pixel resolution.

3.3 Development of Drought Index

Many meteorological indices have been proposed in the literature. However, in this paper we will focus on the cumulative precipitation anomaly index. This index is calculated as the deviation in precipitation from a long-term mean or median for a specific period of time, defined as the proportion of the long term mean or median. The particular time period focused on for this study is the wettest quarter of the agricultural season, as it allows us to capture rainfall dynamics across much of the rainy season in Malawi. This particular index is chosen because, as Thomas et al (2010) emphasize, it is straightforward to calculate, flexible, and does not require another meteorological input such as temperature data.

As such, the average start and end dates of the wettest quarter were computed for each year spanning the 1981 to 2009 period. These dates are provided at the month and dekad level. From there it was possible to find the average start and end date for each plot. I used this to compute the total rainfall within this time frame for each year. As there are two agricultural seasons covered in the survey by different households, there were small differences in the computation of rainfall averages over the two years with plots providing information for the 2008/2009 rainy season using averages over the 1981 – 2007 seasons and plots associated with the 2009/2010 season including the 2007/2008 wet quarter estimates in the long-term average.

There are different cut-offs below which a shortfall in precipitation can be considered a negative rainfall shock, and previous papers using the cumulative precipitation anomaly index use a variety of measures. Though several cut-offs were considered, including one and two standard deviations away from the mean, and thresholds of 10%, 15%, 20%, 25% and 30% away from the mean and median, this thesis focuses on plots that experienced precipitation shortfalls greater than 20% below the median.[3] Also, as can be seen from Figure 2 - a graph representing the distribution of the wettest quarter average for the agricultural season of interest around the long-term median – there is a clear spike in the distribution at a threshold of 20 percent. This approach follows the precedence that has been set by other studies of this nature. Table 1

[3] Key results from all thresholds considered can be found in Appendix A. All thresholds examined yielded similar results.

provides the long-term average rainfall estimates for the period from 1981-2009 as well as seasonal averages for the two seasons of interest. Rainfall estimates are broken down by region (North, Central and South)[4] to illustrate how precipitation varies throughout the country, and by district because the models control for unobserved variability at this level using district fixed effects.

3.4 Using the Negative rainfall shock Index to Measure Impact

The first model examining the impact of negative rainfall shock on agricultural output uses data at the plot-level; it is very simple to merge all of the necessary information with the rainfall data since this is also provided at the plot-level. The remaining models measuring the impact of the negative rainfall shock on welfare utilize household-level rainfall data. The majority of households should have the same or similar rainfall estimates across plots, however given the precision of the rainfall estimates, there is potential for differences if the plots are not located in the same vicinity.

The negative rainfall shock variable will be introduced into the models discussed in the following chapter as a binary variable: simply “1” if a negative rainfall shock was experienced and “0” if the rainfall was not less than 20% below the median.

For the purposes of this analysis, the sample is restricted to households located in rural areas that reported cultivating a plot during the last completed rainy season at the time the questionnaire was administered. Tables 2 and 3 report the incidence of negative rainfall shocks at the plot and household level, respectively. As the tables show, households located in the

[4] The Northern Region includes the districts of Chiti pa, Karonga, Nkhatabay, and Rumphi. The Central Region includes Dedza, Dowa, Kasungu, Lilongwe, Mchinji, Mzimba, Nkhota kota, Ntcheu, Ntchisis, and Salima. The Southern Region includes Balaka, Blanytyre, Chirazulu, Chikwawa, Machinga, Mangochi, Mulanje, Mwanza, Neno, Nsanje, Phalonme, Thyolo, and Zomba.

Southern region of Malawi faced the greatest shortfall in rain during the 2009/2010 wet season with 73.18% of households in this region suffering from a negative rainfall shock whereas the only 1.98% households located in the North experienced rainfall less than the long-term median and 10.17% of households in the Central region experienced a drought. These shortages in rainfall over the two agricultural seasons can also be seen in Figures 2 and 3 mapping the rainfall deficits in the 2008/2009 and 2009/2010 wettest quarters, respectively.

Table 4 presents sample mean values of the value of maize yields per hectare, the value of agricultural output per hectare, per capita consumption expenditures, per capita food expenditures, per capita non-food expenditures, the Shannon Index, and the results from the weighted tests of mean differences by households that did and did not experience negative rainfall shocks. The value of agricultural output was computed using local prices based on sales (if the household sold any goods) when available. Missing values then were replaced using the median price of the enumeration area for the crop of interest and finally, if the values were still missing, the median price for the region. In terms of household-level variables, per capita consumption includes both observed and imputed expenditures and the Shannon Index is a measure of dietary diversity to be discussed in more detail in 3.52. The tests of mean differences in plot-level characteristics were run among all plots reported as cultivated during the 2008/2009 and 2009/2010 rainy seasons, whereas the tests of mean differences in household-level variables were computed among rural households. T-tests of means show that all measures of agricultural output, welfare and food security aside from household per capita consumption expenditures on non-food items are statistically different between households that experienced a negative rainfall shock and those that did not.

3.5 Measuring Food Intake

A number of outcomes would allow us to properly measure food security and nutrition levels among households, however for the purposes of this thesis, and due to the nature of the dataset, I will measure nutrition through food consumption. Two sets of measures are used for this analysis including per capita food expenditures and food consumption diversity.

3.5.1 Per Capita Food Consumption

The survey included detailed consumption modules allowing for a reliable breakdown of consumption expenditures. Total food expenditures per capita are calculated by summing consumption expenditures per household on food items reported in the survey by the household head. Households reported the quantity consumed in the week prior to the survey for a total of 135 food items and these values were aggregated into nine food groups: (i) Cereals, Grains and Cereal Products, (ii) Roots, Tubers and Plantains, (iii) Nuts and Pulses, (iv) Vegetables, (v) Meat, Fish and Animal Products, (vi) Fruits, (vii) Milk/Milk Products, (viii) Fats/Oil, (ix) Sugar/Sugar Products/Honey, (x) Spices/Condiments. Per capita total food expenditures were then calculated by dividing expenditures by the number of household members reported as regularly eating in the home.

3.5.2 Food Diversity

To capture the extent of diversification among food consumption in a household, the second measure of nutrition employed is a food diversity index. The first measure allowed for a broad analysis of food consumed within the household, but because nutrient levels vary between food items and food groups, understanding diversity in food consumption is important. Dietary diversity is often used as a food security proxy in nutrition surveys and has been generally found to be a reliable measurement. There exist many ways to measure food diversity in the literature, however for our purposes we will focus on the Shannon Index that measures the concentration of food groups consumed. It is measured as:

$$\text{Shannon Index} = - \sum w_i \log(w_i)$$

where w_i is the expenditure on food group i. It ranges from zero to the value of the log of the highest number of food groups.

Chapter 4

Empirical Strategy

This chapter describes the models used to assess the impact of experiencing a negative rainfall shock on agricultural production and household welfare in Malawi. I first use a production function to measure any decrease in maize yields or the value of agricultural output that resulted from negative rainfall shocks in the 2008/2009 and 2009/2010 agricultural seasons at the plot-level. The covariate of interest will be whether or not the household has experienced a negative rainfall shock, however this model will also control for other plot, demographic and socioeconomic characteristics that may influence output.

It is important to note that the occurrence of a drought in a locality is most likely correlated with the likelihood of it occurring in the first place. This increased probability in itself may affect yields, the value of agricultural output and the level of consumption as households in drought prone areas have most likely taken some action to adapt to these conditions, such as accumulated asset loss at the household or community level (Thomas, Christiansen et al 2010). Generally studies use panel data to account for this unobserved heterogeneity across communities, however sufficiently long panels are often not available. For the purposes of this thesis, I will use a cross-section to observe short-run impacts of rainfall shocks accounting for heterogeneity concerns through the inclusion of a comprehensive set of agro-climatic and community characteristics. Both the agricultural production model and the household welfare model will include large sets of independent variables in an attempt to control for the unobservable characteristics across plots and households.

4.1 Agricultural Yields Model

Production function analysis was adopted to estimate the effects of negative rainfall shocks on the value of agricultural output. In order to investigate the impact of rainfall variability on agricultural production in Malawi I use a multiple regression model that measures the impact of a negative rainfall shock on agricultural yields while controlling for other variables that influence the value of agricultural output. The equation used for the estimation is given as the following:

$$\ln \mathbf{Y}_{i,h,d} = \beta_0 + \beta_1 \mathbf{S}_{i,h,d} + \beta_2 \mathbf{X}_{h.d} + \beta_3 \mathbf{P}_{i,h,d} + \rho_d + \varepsilon_{h.d} \qquad (1)$$

where i represents a plot; h denotes a household; d denotes the district; $\mathbf{Y}_{h,d}$ represents a measure of agricultural production; $\mathbf{P}_{i,h,d}$ is a vector of plot characteristics; $\mathbf{S}_{h.d}$ is the rainfall shock variable; $\mathbf{X}_{h,d}$ is a vector of household characteristics; ρ_d are district level fixed effects which control for all locality characteristics; $\varepsilon_{h.d}$ represents the error term.

The outcomes of interest are maize yields per hectare and the log of the value of agricultural output in Malawian Kwacha per hectare. The control variables used in the model are important not only because they represent additional factors that influence output, but also because they allow for a proper examination of which plot and household characteristics best enable farms to cope with negative rainfall shocks. Below is a detailed look at the other variables thought to explain differences in yields and the value of agricultural output per hectare across plots.

4.1.1 Control Variables

Plot Characteristics

The detailed agricultural questionnaire included in the IHS3 survey allows for an in-depth look at the characteristics of the plot and I include the following variables: (i) the logarithm of the area of the plot in hectares and its squared term; (ii) the distance from the plot to the household (in kilometers); (iii) a dummy equal to 1 if there is a mixed crop stand on the plot (if the plot is intercropped).

Inputs

To account for differences in inputs I use (i) the logarithm of the amount of inorganic fertilizer used on the plot in kilograms per hectare; (ii) a dummy equal to 1 if pesticides or herbicides were used on the plot.

The model accounts for discrepancies in labor inputs available at each plot through the use of the following variables: (i) the logarithm of the labor input of adult, male household members in hours per hectare; (ii) the logarithm of the labor input of adult, female household members in hours per hectare; (iii) the logarithm of the labor input of children in the household; (iv) the logarithm of the hired labor input; (v) the logarithm of the exchange labor input; (vi) the logarithm of the family manager labor in hours per hectare and its squared term. Only labor inputs used for non-harvest activities such as land preparation, planting, weeding and fertilizing are included to control for possible endogeneity issues; the amount of labor required for harvesting is partially determined by the rainfall received during the wet season.

Household Human Capital

The agricultural production model controls for differences in human capital through a variety of variables relating to the composition of the household and characteristics of the plot manager. The following variables are used for this purpose: (i) the household size; (ii) the household dependency ratio computed as the number of people in the household aged 0-14 added to those aged 65 and over. This sum is then divided by the number of people aged 15-64 and then multiplied by 100; (iii) a dummy variable equal to 1 if the household had access to extension services during the rainy season of interest. Approximately 16% of households interviewed received advice from an extension service, with about 43% of this group receiving assistance from a Government Agricultural Extension Service, 38% getting advice from a media source such as television or radio, and the remainder taking advantage of social networks such as neighbors or relatives to obtain information.

As the plot manager maintains much of the control over the plot, the characteristics of the manager can greatly influence the performance of the plot and differences among managers are controlled for through the use of (i) the age of the manager; (ii) the number of years of schooling of the manager; (iii) a dummy equal to 1 if the manager is female.

Household Physical Capital

To account for discrepancies in asset position I use (i) a wealth index developed by the World Bank. In this particular case, the asset index was computed using principal component analysis, based on ownership of non-agricultural goods and housing conditions[5]; (ii) an

[5] The asset index is based on principal component analysis of whether or not the household owns their residence, the number of rooms in the dwelling, whether they own a number of durable goods (mortar, bed, table, chair, fan,

agricultural index also computed by the World Bank[6]. This was developed to represent agricultural implements and machinery access.

Location

The model uses district-fixed effects to capture differences across regions and areas of Malawi. The model also controls for the agroecological zone in which the plot is located through dummies representing (i) plots in a tropic-warm/semiarid zone; (ii) plots in a tropic-warm/subhumid zone; (iii) plots in a tropic-cool/semiarid zone. Plots in a tropic-cool/subhumid zone make up the omitted category.

4.2 Household Welfare Model

The impact of shocks on household welfare is often assessed by augmenting a standard reduced form consumption regression with explicit measures of the shocks themselves. Similarly, models of food expenditure and calorie consumption generally include sets of exogenous household and community variables expected to influence household decision making with respect to food expenditures and intake. The estimation strategy for this set of analyses follows these standard models and uses the household-level data to estimate the following equation:

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radio, tape/CD player, TV/VCR, sewing machine, paraffin/kerosene/electric/gas stove, refrigerator, bicycle, car/motorcycle/minibus/lorry, beer brewing drum, sofa, coffee table, cupboard, lantern, clock, iron, computer, fixed phone line, cell phone, satellite dish, air-conditioner, washing machine, generator, solar panel, desk) and their housing conditions (quality of outer walls, roof and floor, access to toilet, access to water)

[6] The agricultural index is constructed similarly to the asset index and is based on principal component analysis of whether or not the household owns a number of farm implements, machinery and/or structures (hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, watering can, ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, grain mail, chicken house, livestock kraal, poultry kraal, storage house, granary, barn, pig sty)

$$\ln \mathbf{W}_{h,d} = \beta_0 + \beta_1 \mathbf{S}_{h,d} + \beta_2 \mathbf{X}_{h.d} + \rho_d + \varepsilon_{h.d} \quad (2)$$

where h denotes a household; d denotes the district; $\mathbf{W}_{h,d}$ represents a measure of household welfare; $\mathbf{S}_{h.d}$ is the rainfall shock variable; $\mathbf{X}_{h,d}$ is a vector of other factors explaining consumption levels such as household characteristics and assets; ρ_d are district level fixed effects which control for all locality characteristics; $\varepsilon_{h.d}$ represents the error term.

A number of dependent variables will be used to assess the impact of negative rainfall shock on household welfare. Overall consumption levels are measured by per capita consumption expenditures. To study the impact of negative rainfall shocks on nutrition levels, a number of possible outcomes that were previously discussed will be examined including the consumption expenditures per capita on food and the Shannon Index, which is used as a basic measure of food diversity.

The variables listed below make up the vector of other factors influencing consumption levels, $\mathbf{X}_{h,d}$, and are used as a representation of a household's composition, characteristics of the household head and an asset index representing a household's wealth. These are all variables that are thought to explain overall household consumption expenditures and nutrition levels.

4.2.1 Control Variables

Household Composition

Factors representing human capital that may influence household consumption are captured by (i) the household size (ii) the number of children in the age category of [0,5] as a percentage of the total household members; (iii) the number of children in the age category of [6-14] as a percentage of the total; (iv) the number of male household members ages [15-39] as a percentage of the total; (v) the number of female household members ages [15-39] as a percentage of the total; (vi) the number of male household members in the age category of [40,59] as a percentage of the total; (vii) the number of female household members in the age category of [40,59] as a percentage of the total.

Household Head Characteristics

A number of characteristics of the household head are used including (i) age of the household head; (ii) a dummy variable equal to 1 if the head is female; (iii) the maximum years of schooling attained by a member of the household. The education level of the household head's father is used as an additional control for human capital and is represented by (i) a dummy equal to 1 if the highest level educational qualification acquired by the father is primary school; (ii) junior primary school; (iii) Malawi School Certificate of Education (MSCE) and above.

Physical Capital

I account for differences in household wealth through (i) the wealth index described earlier for the agricultural production model. For this model, the sample has been broken down into wealth quintiles using the asset index and those in the poorest quintile are used as the control group to allow us to compare consumption and dietary diversity across populations. To represent a household's integration into the local economy, the household data were further augmented with the (i) distance of the household to the nearest main road (in km); (ii) distance of the household to a city or the nearest locality with more than 20,000 inhabitants (in km).

Household Income

To control for differences in sources of income I include (i) a dummy equal to 1 if the household has any nonfarm income (wage, ganyu, self-employment); (ii) a dummy equal to 1 if the household receives other transfers or safety net help; (iii) a dummy equal to 1 if the households has borrowed any cash or inputs within the last 12 months to try and account for access to credit.

Community Assets

To reflect public services available in the community I take into account (i) a dummy equal to 1 if there is an agricultural extension officer present in the community; (ii) a dummy equal to 1 if there exists a bank or microfinance institution within the community.

4.3 Heterogeneity of Impact

In order to determine whether the impact of a negative rainfall shock differs among different populations and to test for the relevance of specific policy measures, equations (1) and (2) can be expanded to include interaction terms as follows:

$$\ln\mathbf{Y}_{i,h,d} = \beta_0 + \beta_1 \mathbf{S}_{i,h,d} + \beta_2(\mathbf{S}_{h,d} * \mathbf{Z}_{h,d}) + \beta_3\mathbf{Z}_{h,d} + \beta_4\mathbf{X}_{h.d} + \beta_5\mathbf{P}_{i,h,d} + \rho_d + \varepsilon_{h.d} \qquad (3)$$

$$\ln\mathbf{W}_{h,d} = \beta_0 + \beta_1 \mathbf{S}_{h,d} + \beta_2(\mathbf{S}_{h,d} * \mathbf{Z}_{h,d}) + \beta_3\mathbf{Z}_{h,d} + \beta_4\mathbf{X}_{h.d} + \rho_d + \varepsilon_{h.d} \qquad (4)$$

where i represents a plot; h denotes a household; d denotes the district; $\mathbf{Y}_{h,d}$ represents a measure of agricultural production; $\mathbf{W}_{h,d}$ represents a measure of household welfare; $\mathbf{S}_{h.d}$ is the rainfall shock variable; $\mathbf{Z}_{h,d}$ identifies the type of household or plot; $\mathbf{X}_{h,d}$ is a vector of household characteristics; $\mathbf{P}_{i,h,d}$ is a vector of plot characteristics; ρ_d are district level fixed effects which control for all locality characteristics; $\varepsilon_{h.d}$ represents the error term.

A number of key plot and household characteristics and household-level adaptation decisions that could serve to mitigate the impact of a negative rainfall shock are studied. The analysis looking at the value of agricultural output studies differences between the primary crops grown on the plots and whether or not different agricultural-ecological zones impact production levels. For the household-level analysis on household welfare I will examine a variety of characteristics such as the household’s access to non-farm income, access to credit, and the highest education level achieved in the household.

Chapter 5

Results and Discussion

In the following chapter I present the results from my analyses of the impacts of negative rainfall shocks on maize yields, value of agricultural output and on the household-level welfare outcomes of households.

5.1 Impact of Rainfall Variability on Agricultural Yields

To examine the extent to which droughts impact agricultural production, I first estimate equation (1) using the log of maize yields per hectare. As maize is the primary staple crop in Malawi this allows for a measure of the initial impact of the rainfall shock on agricultural production excluding the price effects influencing the value of output. I then estimate equation (1) using the log of the value of agricultural output in Malawian Kwacha per hectare. Table 7 presents the results from this regression using our survey sample weights with clustering at the enumeration area level.

Table 7 presents the results from the full regression on the log of maize yields per hectare in the first specification and the second specification presents the results for the value of agricultural output. The full regression includes variables representing inputs such as inorganic fertilizer, pesticides and labor as well as the primary type of crop on the plot in an attempt to account for the unobservable heterogeneity across plots. Our main results of interest are as expected with a significant decline in both maize yields and the value of agricultural output resulting from a negative rainfall shock. Plots experiencing rainfall greater than 20 percent less than the long-term median suffer a 21 percent decrease in maize yields and a 17.6 percent loss in the value of agricultural output per hectare.

I then perform a robustness check to get a sense how of my main outcome of interest, the negative rainfall shock, behaves across five different specifications. I first run the model with only the negative rainfall shock variable. In the second specification I include district fixed effects; in the third I add inputs; in the fourth specification I add dummies representing the primary crop grown on the plot and finally, the fifth specification represents the full model discussed previously. As the results in Table 8 show, even with the regression in its most basic form there is a significant 31.4 percent decrease in the value of agricultural output for households that experienced a negative rainfall shock. As the range of our coefficient is so small across the specifications (22.4 percent in the second with only district fixed effects included and 18 percent in the last), it is clear that regardless of the variables included, households experiencing a negative rainfall shock suffered a loss in terms of agricultural production. Also, as the magnitudes of the drought coefficient changes only slightly across the five specifications when adding independent variables such as inputs, it is clear that the many control variables I use to attempt to capture any unobservable factors influencing production are exogenous to drought. Though the survey does not provide data regarding farmers' access to information regarding weather or expected rainfall patterns, it seems that any information they may have is not influencing their production decisions.

Though the independent variables included in the model are intended to control for any unobservable factors that may impact our outcomes of interest aside from the negative rainfall shock and do not imply causal relationships, interesting relationships do result. The relationship between the log of plot area and the value of output reveals the inverse relationship between farm size and productivity often found in developing countries. The logged quantity of inorganic fertilizer used has a positive impact on the value of output, with any use of pesticides on the plot showing an increase of 33.7 percent in output. All labor inputs included show positive and significant impacts on the value of agricultural output aside from the variable representing that of the children in the family, with male laborers shown to be 80 percent more effective than female labor.

The type of crop grown on the plot impacts the value of output as evidenced by the results; observations that report the primary crop grown on the plot as tobacco show a large increase, 112 percent, in the value of output. Plots with hybrid maize as the primary crop grown on the plot also have a significant 7.7 percent increase in the value of agricultural output and the ability of these two crop types to protect agricultural production from a drought will be tested in Section 5.3. Households with intercropped plots also maintain higher production levels with a 12.4 percent increase in the value of output.

Similarly, households reporting greater physical capital through both the wealth index and the agricultural machine index fared better in terms of agricultural production. The coefficient for the wealth index showed an increase of 7.6 percent in maize yields in the first specification and 6.6 percent in the value of agricultural output. In terms of the agricultural index representing ownership of farm implements and machinery, the coefficients showed a 3.7 percent and 3.4 percent increase in maize yields and the value of agricultural production, respectively.

The results of this model also reflect the importance of human capital to agricultural production. Households that have received advice from an agricultural extension service, whether it is associated with the government, a non-governmental organization or an agricultural cooperation, show a higher yields and value of output along with plots run by a manager that attained a higher level of schooling positively impacting yields. Despite the strong positive impact of access to agricultural extension services on the value of agricultural output, it is important to bear in mind that this is not necessarily a causal relationship as this variable is highly endogenous. It is possible that the allocation of extension services is not random across households and communities and this can distort results (Dercon et al 2007). Households that are selected may be those more likely to adopt the suggested practices of the agricultural extension services. Based on the results the ability of a household to cope with and recover from a shock is largely determined by its access to resources provided by governmental assistance programs or infrastructure so it is important to note and control for the possible effect this has on the production; however, this variable must be interpreted with caution as, again, government assistance programs are often targeted to already poor areas.

The relationships found between the characteristics of the plot manager and yields and output are unsurprising given the body of literature on the relationship between gender and agricultural production. The results show that plots managed by females experience a significant decrease in maize yields and the value of agricultural output of 10 and 7.6 percent, respectively. Many studies looking at the differences between male and female production levels show that there is evidence of allocative inefficiency within households which may result in lower productivity among female farmers. (Quisumbing, 1996).

5.2 Impact of Rainfall Variability on Household Welfare

To examine the impact of a drought on household consumption, I estimate equation (2) using numerous specifications. The first measurement of household consumption used is the logarithm of per capita expenditures on all goods.[7] This includes expenditures on food and beverages, alcohol and tobacco, clothing and footwear, housing and utilities, furnishing, health, transport, communications, recreation, education, vendors and cafes and other miscellaneous goods and services. In order to determine the effect that droughts have on different categories of consumption, I use the logarithm of per capita food expenditures and non-food expenditures. The measure of food expenditures per capita is also used to measure food security and nutrition along with the Shannon Index.[8]

Aside from the drought variable, I include the household composition, characteristics of the household head, a wealth index, community characteristics and controls for the district in which the household is located to properly model household consumption as discussed in the previous chapter.

Table 9 presents the results from this regression using our sample survey weights with clustering at the enumeration area level. The first striking, but expected, result is the significant negative impact of negative rainfall shocks on all measures of consumption and dietary diversity aside from nonfood consumption expenditures. On average, households that faced a negative rainfall shock during the last rainy season prior to the IHS3 survey report per capita expenditures to be 4.4 percent lower than households that received adequate rain. Interestingly, it appears that households may be better able to protect their consumption expenditures on nonfood items rather than food expenditures. Per capita expenditures on food are 5.4 percent lower for households that faced a negative rainfall shock. This decline in nutrition through food expenditures is also

[7] Following the example of Skoufias, Vinha and Conroy (2011) I also measured household consumption as per capita expenditures on all goods excluding health related items. This is done because most health spending follows illness, therefore it is not welfare improving. The results were unchanged from total expenditures so have not been included.

[8] I also measured food security through the number of calories consumed per capita and the results were insignificant.

reflected in the dietary diversity of households as those that experienced a negative rainfall shock achieved a dietary diversity score on the Shannon Index that is lower than the non-affected group.

In terms of household composition and characteristics of the household head included in the model, though these were included to control for unobservable factors, they display the relationships that one would suspect based on the literature. Other notable results include the highest level of education achieved by any member of the household as well as the education level of the father of the household head. As would be expected, households with higher education levels show an increase in consumption at all levels. Not surprisingly, households in higher wealth quintiles maintain higher levels of consumption expenditures and nutrition as the results show significant and increasing results across groups.

In an attempt to control for the endogeneity regarding a household's access to agricultural extension services, the variable used for this model represents access to this public assistance program at the community-level rather than the household-level. As with the agricultural production model, this variable appears to have a positive impact on consumption expenditures. Though again, this must be interpreted with caution.

5.3 Heterogeneity of Impact

Though the results discussed in sections 5.1 and 5.2 allow for overall analysis of the impact of negative rainfall shocks on measures of welfare, the average impacts may mask differences in response between types of plots and households to these weather shocks. The estimation of equations (3) and (4) allow us to examine plot and household characteristics that may mitigate or exacerbate the impact of a severe negative rainfall shock and the effectiveness of farm-level adaptation practices to rainfall variability.

Household-level adaptation decisions can greatly impact household welfare outcomes and, in general, these practices can be categorized into the following groups: (a) income diversification, including non-farm income and mixed crop-livestock farming systems; (b) crop diversification; (c) investment in soil and water conservation and management; and (d) use of irrigation (Deressa, et al 2008; Nhemachena and Hassan 2009). To test the success of households taking advantage of some of these practices I first use equation (3) to look at whether or not different types of crops are better able to survive a severe negative rainfall shock and if plots located in different agroecological zones protect the value of agricultural output on a plot. At the household-level, farmers may be able to better protect their consumption levels through other sources of income and equation (4) is used to determine the extent to which this is a successful strategy.

Household decisions on how to adapt to weather variability are influenced through a wide range of household and community-level characteristics that reflect a household's access to new technologies and information and the resources they have available. Maddison (2007) found that, in a study of 11 African countries, although experienced farmers are more likely to perceive climate change, it is educated farmers who are more likely to respond by making at least one adaptation. Deressa and Hassan (2008) identified the major methods used by farmers to adapt to climate change in Ethiopia and the factors that influenced their choice of methods included "the level of education, gender, age, and wealth of the household head; access to extension and credit; information on climate, social capital, agroecological settings, and temperature". To get a sense of how these factors may influence the ability of a Malawian household to mitigate the impact of a short-term change in climate variability, I examine the difference in welfare levels through a variety of household characteristics including whether or not the household has any source of non-farm income or access to credit, and the highest level of education attained in the household. Table 12 reports the results of interacting these terms with the negative rainfall shock.

5.3.1 Plot Characteristics

To help protect their agricultural income, farmers may choose to diversify their crops and plant more drought-resistant crops or varieties of crops. To capture differences in the impact of the negative rainfall shock on different types of crops, I have run the second specification from Table 7 on plots planting local maize, hybrid maize, tobacco or groundnuts separately for each of these crops. As shown in Table 10, households with tobacco as the primary crop planted appear best able to protect their agricultural income from the impact of a drought as this coefficient only shows a 6.9 decrease in the value of output resulting from the negative rainfall shock. Hybrid maize also appears better able to withstand the negative rainfall shock than local maize as these coefficients represent a 16.3 percent and 21.4 percent decrease in output, respectively. Groundnuts are least able to handle a drought during the agricultural season and show 41.1 percent decrease in the value of agricultural output per hectare. Testing to see if these differences are significant reveals that the coefficient for tobacco is significantly smaller than those of the other three primary crops examined. Surprisingly, the difference between local maize and hybrid maize is insignificant so households that planted hybrid maize in the agricultural seasons of interest did not appear to have as much of an advantage over households planting local maize - a variety that is generally thought to be less drought resistant.

The ability of plots with tobacco as the primary crop grown to better mitigate the impact of a negative rainfall shock is logical as stems from tobacco need less water than other crops. Findings along these lines may encourage more farmers to become involved in tobacco production as opposed to maize and groundnuts. The tobacco industry in Malawi plays an important role in their economy both on large scale estates but also with smallholder farmers and an estimated 75 percent of the Malawian population is dependent on tobacco farming. Involvement in the production of tobacco, however, poses health ricks and for farmers located in rural areas it can be difficult to reach local tobacco markets given the poor infrastructure and access to roads throughout much of Malawi.

In order to extract further disparities in the value of agricultural output across plots, I run the full model on the value of agricultural output per hectare for each of the four agroecological zones in Malawi. This reveals that plots located in a tropic-cool/semiarid agroecological zone seem best able to weather the impact of a severe shortfall in rain with tests revealing that this difference in the coefficient in comparison to the two other agroecological zones with significant coefficients.

5.3.2 Household Characteristics

Households that are fully dependent on rainfed agriculture for their livelihood are expected to suffer from a severe rain shortfall with this reflected in a decrease in consumption expenditures, however if a rural household in Malawi is only partially dependent on agriculture for their income and has some source of nonfarm income, coming from areas such as wage, ganyu or self-employment, they may be able to better protect their consumption from the shock. Table 12 shows that, overall, households experiencing a negative rainfall shock that do not have any source of nonfarm income experience a significant 9.5 percent loss in consumption expenditures. As suspected, households with access to nonfarm income that did not experience a shock report an 8.4 percent increase in consumption; however, the interaction between these two variables is insignificant.

Households with access to credit, or more specifically, households that borrowed cash or inputs within the last 12 months prior to the interview show results that at first seem contradictory. The interaction term between this variable and the shock dummy shows a 12.3 percent decrease in consumption expenditures with households experiencing a shock that did not have access to credit only showing a 9.7 percent decrease in consumption. However, we must take into account the overall 14.5 percent advantage in consumption expenditures that households with access to credit have in the first place that serves to balance out the impact of the shock. A test to see if the sum of the coefficients for the interaction term and its components is equal to zero reveals this sum is, indeed, equal to zero therefore showing that the small sample of households with access to credit were able to cancel out the impact of the negative rainfall shock.

5.3.3 Individual Characteristics

As shown in Table 11, households containing individuals that have attained higher levels of education seem that they may be better able to cope with experiencing a drought with the main effect of a higher level of education in the household showing a 1.4 percent increase in consumption expenditures. Also, based on findings in the literature it could be surmised that better-educated household members would be able to properly adapt to weather variability and protect their agricultural earnings from a drought. However, given that the interaction between our negative rainfall shock and the variable representing the highest level of education attained in the household is insignificant for both welfare measures, it appears that in our sample, having a higher education level does not necessarily prepare farmers to adapt to weather variability.

5.4 Additional Discussion

It is clear from these results that the effects from a negative rainfall shock reverberate throughout the household. The first sign of the shock is in the form of the decline in the value of agricultural output per hectare and is then shown through the decrease in overall household-level consumption expenditures, food expenditures and dietary diversity. As shown in the results from the regressions, households in rural Malawi that face a negative rainfall shock are, on average, unable to shield their consumption expenditures from this loss in agricultural income.

As discussed in other studies of a similar nature, the existence of irrigation systems can help to mitigate the negative impact of a drought. Given the small percentage of farms in Malawi that utilize irrigation systems and that only .38 percent of our sample employed any type of irrigation system (divert stream, bucket, hand pump, treadle pump, motor pump), it was implausible to include this variable in the plot-level and household-level regressions. However, this is an area that can guide policy decisions in how best to prepare the rural population for rainy seasons that do not receive adequate rainfall.

The plot-level results from examining heterogeneity across the primary crop planted on the plot and the agroecological zone in which the plot is located provide some intuition as to the characteristics that may better enable a household to mitigate the impact of experiencing a drought as tobacco farmers are, on average, better off along with those located in a tropic-cool/semiarid agroecological zone. Results looking at the heterogeneity of impact across household, individual and community characteristics at the household-level, however, are not nearly as successful in guiding any sort of policy considerations for possible mitigation strategies. The results from the majority of these interaction effects are insignificant though this very well could result from the endogenous nature of many of the independent variables included in the regression.

Chapter 6

Conclusion

6.1 Conclusion

In rural areas highly dependent on agricultural production, the level of rainfall and its variability are critical for subsistence. This is especially true in Sub-Saharan Africa, in countries such as Malawi, where agriculture is predominantly rain-fed. Through the use of the empirical strategy outlined in Chapter 4, I was able to meet the two objectives of this thesis: (i) to model the effects on agricultural production and household welfare of an objectively-measured, severe rain shortfall in Malawi and (ii) to identify plot and household characteristics that serve to mitigate or exacerbate the effects of experiencing a negative rainfall shock.

I have used data from the 2010 - 2011 Malawi Integrated Survey on Agriculture that includes several indicators of production levels and welfare, such as maize yields, the value of agricultural output, consumption expenditures and the Shannon Index. This augmented with our measure of severe drought derived from a 30-year complete weather station time series allowed for the proper analysis of the overall impact of experiencing a severe negative rainfall shock on agricultural households in rural Malawi.

Among the key findings of this thesis is that severe negative rainfall shocks have a significant impact on almost all of the dimensions of welfare studied. On average, households in rural Malawi are unable to mitigate the impact of a drought in the agricultural seasons of interest as shown in the 31.6 percent decrease in maize yields, the 18 percent decrease in the value of agricultural output, the 4.4 percent decrease in overall per capita consumption expenditures, the 5.4 percent decrease in food expenditures, and the decrease in dietary diversity. There are, however, plot and household characteristics that may better prepare households for coping with the threat to agricultural income that comes from experiencing a drought. Based on the results it seems that farmers planting tobacco in our reference seasons of interest were in a position to better protect their agricultural earnings from the impact of a drought, as well as farmers located in a tropic-cool/semiarid agroecological zone. Also, households with access to credit that experienced a negative rainfall shock were able to protect their consumption levels.

6.2 Limitations of this Study

Despite the strong focus on agriculture, a report on the LSMS-ISA project acknowledges that significant gaps exist in the questionnaire design of these surveys with regard to adaptation to weather variability. After a review of the questionnaires used in the LSMS-ISA project countries, the report identifies four sources of data gaps, including "(a) lack of data collection on farmers' perceptions of weather variability; (b) insufficient coverage of questions related to adaptation to weather variability and local water resource stress; (c) no data collection on households' access to weather forecast information before planting seasons; and (d) lack of survey instruments for collecting local water resource data." This study would benefit from additional questions on these topics as it could then take into account the extent of the information that farmers have on rainfall predictions for the agricultural season and how they respond to this knowledge.

This study would also benefit from the availability of panel data to study the impact of negative rainfall shocks over time. Though the detailed information provided in the IHS3 dataset allows for a short-term look at the impact of a negative rainfall shock on welfare, a panel dataset would allow the models to capture the unobserved heterogeneity across plots, households, and communities and better measure the negative effects of a drought.

6.3 Future Work

This thesis provides the preliminary analysis and a solid base for future work that will likely go in two possible directions. First, this research could contribute to the body of literature exploring links between agriculture and household and child welfare in the context of diversified livelihood strategies and market failures (non-separability). The work would employ a 2sls strategy with the IRE rainfall time series used in this thesis and the drought index that was subsequently developed used as a possible instrument representing agricultural production levels. Rainfall is often used as an instrument for agricultural income since rainfall directly affects agricultural production but is itself unaffected by the economy. Household involvement in agriculture is typically endogenous as it is difficult to determine if the presence and composition of agricultural involvement impact welfare and nutritional outcomes or if welfare levels influence production. Due to the exogenous nature of rainfall, the instrumental variable approach could be used to address this endogeneity concern and provide consistent estimates.

The second possible direction for this work is a paper creating guidelines for the measurement of seasonal drought. Though the previous studies discussed in this thesis that developed objective measures of weather disasters provided some guidance as to the procedure to follow, there is no clear strategy defined in the literature and a paper of this nature would help to fill this void. Many household surveys provide subjective assessments as to whether or not a farmer reports having experienced a drought in the season of interest, however as outlined earlier in this thesis, these assessments can lead to biased estimates as the likelihood of a respondent reporting having experienced a drought stems from their ability to cope with this rainfall shortage. Given this endogeneity concern, objectively defined measures of inadequate rainfall likely provide a more accurate representation of households experiencing droughts.

The work would outline the steps involved in developing a drought index or objective measure of adequate rainfall, and highlight the decision making process that the researcher should follow. The most important aspect of developing a drought index is the quality and resolution of the rainfall data available. The rainfall data used in this thesis provided extremely reliable estimates thanks to the IRE method (that takes into account climatology) developed by USGS, and this enabled me to look at rainfall over a complete 30-year period. Often rainfall estimates of this 5x5 resolution and 30-year duration are not available, especially in developing countries, so researchers must rely upon the best data available. The variety of estimates for Malawi will allow for a proper comparison of these measures to determine whether or not the precision of the data affects the results.

Regardless of the precision of the data available, there needs to be a procedure for determining the reference period for the time trend, and the threshold for defining a drought. In the case of this thesis, the rainfall data available determined the long-term period of interest (30 years), but the reference period and threshold were chosen based on knowledge of Malawi and using the precedence set in previous literature. The importance of the wettest quarter to the Malawian agricultural season creates an obvious time frame for the focus of this analysis, but it would have been possible to measure rainfall over the entire year or the full rainy season, and for papers of this nature in different settings, other reference periods may be more relevant. Overall, this paper could contribute to the economic literature by setting a gold standard for measuring rainfall shocks to guide future work in this area.

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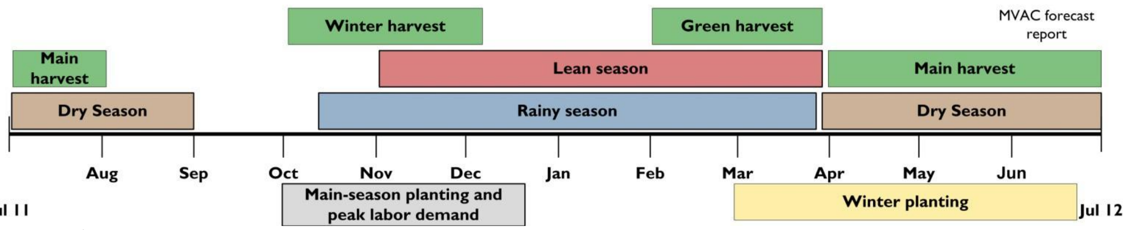
Tables and Figures

Figure 1. Seasonal calendar and critical events timeline



Source: *FEWS NET*

Figure 2. Distribution of Rainfall Around Long-term Median

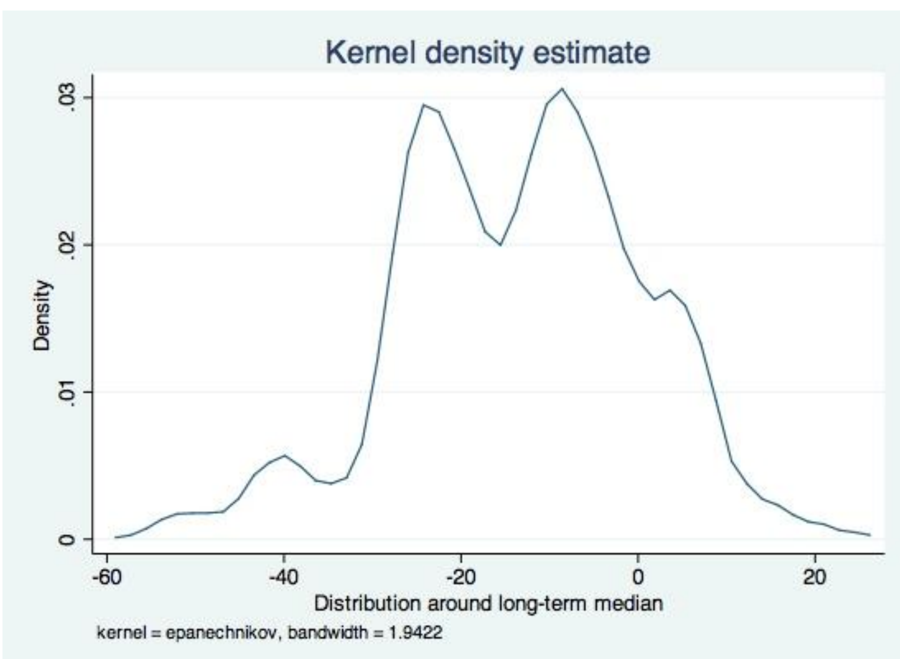


Figure 3. 2008/2009 Wettest Quarter Rainfall Deficit

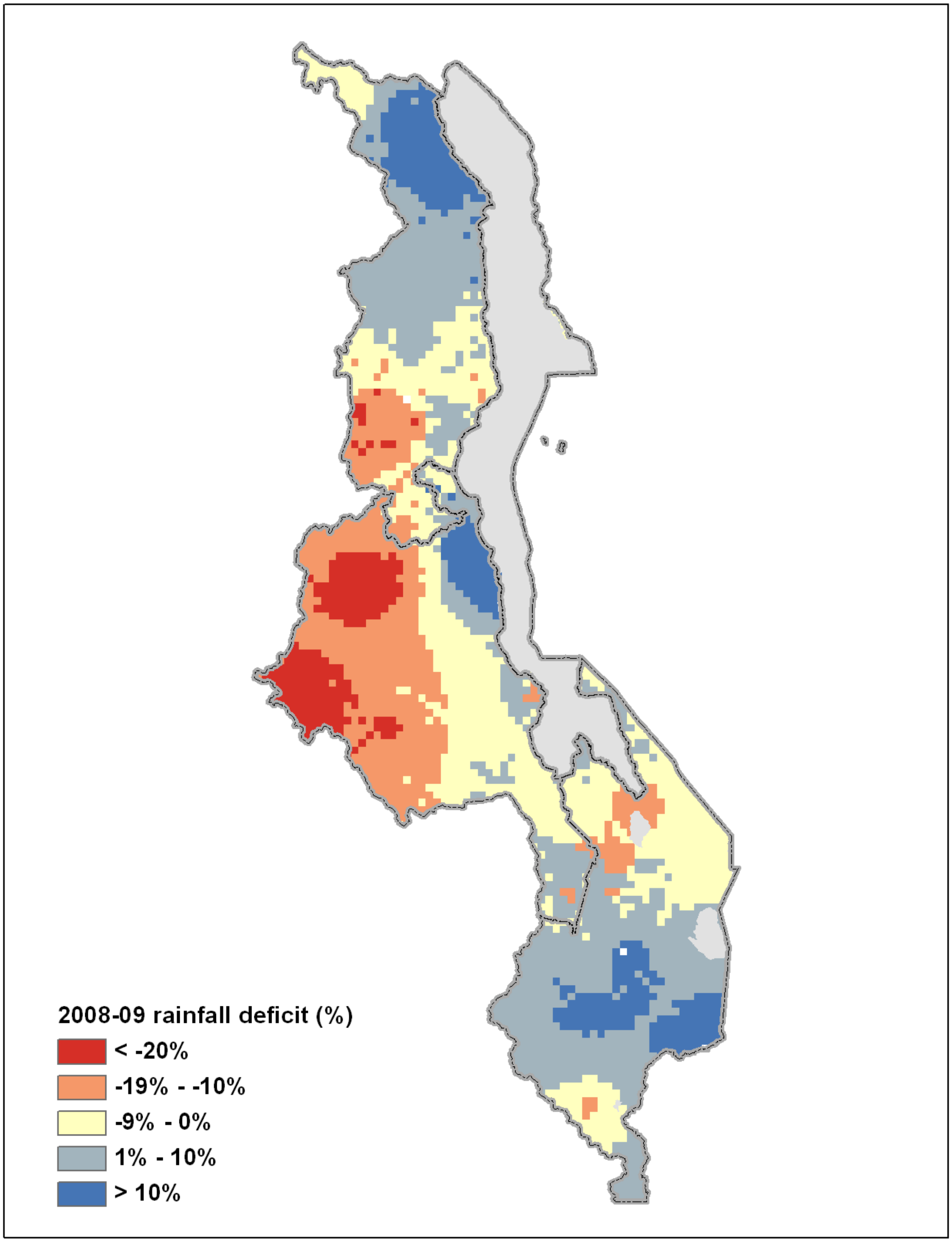


Figure 4. 2009/2010 Wettest Quarter Rainfall Deficit

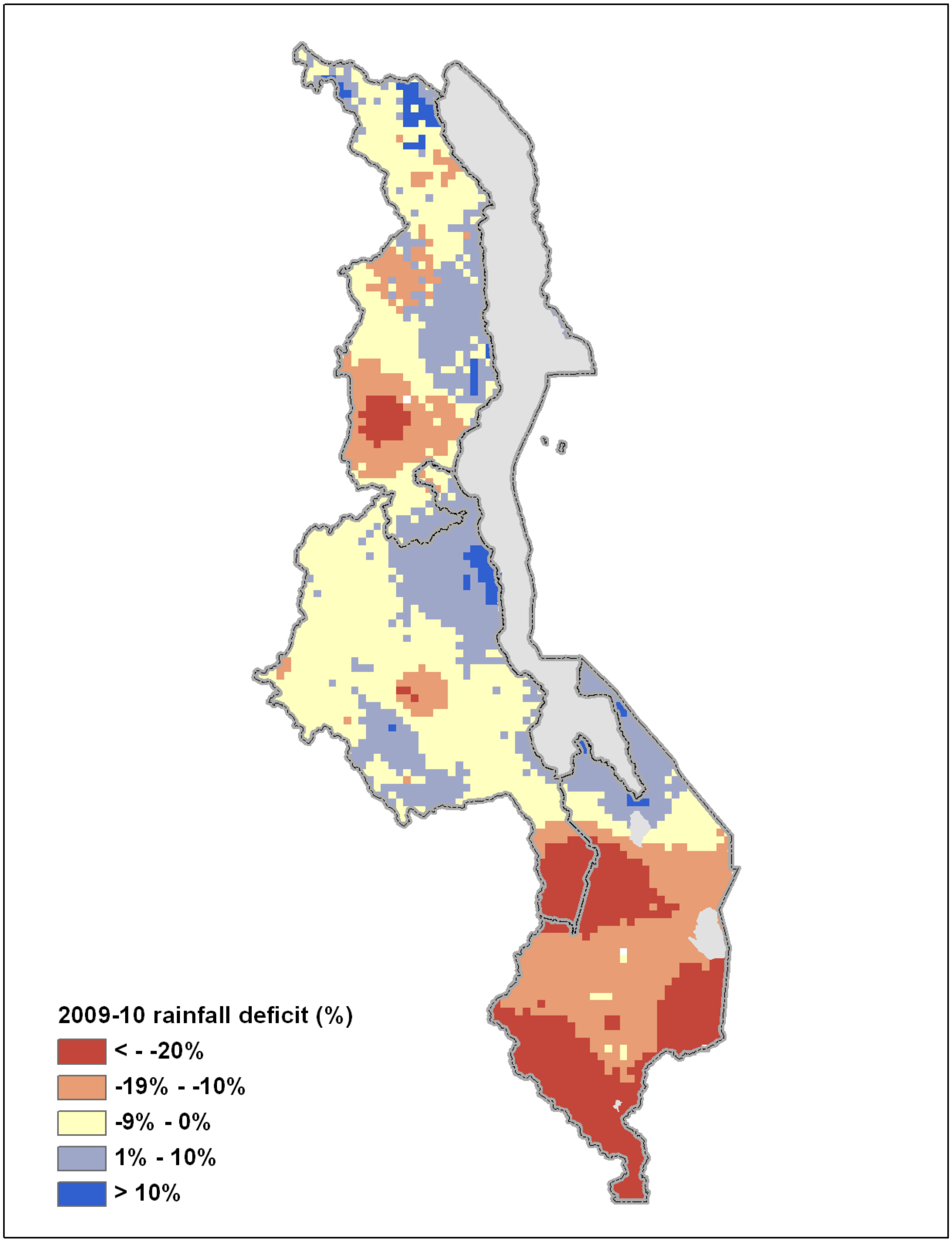


Table 1. Long-Term and Seasonal Rainfall Estimates by Region (in mm)

	North		Central		South	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
2008/2009 Season						
Long Term Wet Season Avg Rainfall	607.64	80.03	683.57	81.75	680.18	76.72
Long Term Wet Season Rainfall (std. dev.)	122.77	36.87	139.32	41.08	178.26	22.13
Long Term Wet Season Median Rainfall	604.5	76.17	675.23	78.64	704.24	83.96
08/09 Wet Season Average	637.43	91.38	675.32	170.67	717.59	105.14
Number of Households	**141**		**444**		**887**	
2009/2010 Season						
Longer Term Wet Season Avg Rainfall	657.6	119.91	658.04	59.56	686.1	74.97
Long Term Wet Season Rainfall (std. dev.)	126.8	40.9	115.22	26.93	177.59	21.24
Long Term Wet Season Median Rainfall	651.97	113.96	656.68	60.34	708.98	83.82
09/10 Wet Season Average	658.64	145.07	607.86	95.62	538.7	96.91
Number of Households	**1164**		**3216**		**3621**	

***Districts in each region noted on page 17**

Table 2: Plot-Level Rainfall Shocks

	Total	North	Central	South
2008/2009 Season				
No Shock	2,277 (97.43%)	242 (100%)	690 (93.50%)	1,345 (99.12%)
Negative Rainfall Shock (>20% less than median)	60 (2.57%)	0 (0%)	48 (6.50%)	12 (0.88%)
Number of Observations	**2,337**	**242**	**738**	**1,357**
2009/2010 Season				
No Shock	8,670 (66.47%)	2,156 (88.91%)	5,083 (93.20%)	1,431 (27.71%)
Negative Rainfall Shock (>20% less than median)	4,374 (33.53%)	269 (11.09%)	371 (6.80%)	3,734 (72.29%)
Number of Observations	**13,044**	**2,425**	**5,454**	**5,165**

Table 3: Household-Level Rainfall Shocks

	Total	North	Central	South
2008/2009 Season				
No Shock	1,433 (97.35%)	141 (100%)	414 (93.24%)	878 (98.99%)
Negative Rainfall Shock (>20% less than median)	39 (2.65%)	0 (0%)	30 (6.76%)	9 (1.01%)
Number of Observations	**1,472**	**141**	**444**	**887**
2009/2010 Season				
No Shock	6,240 (60.88)	1,141 (98.02%)	2,889 (89.83%)	971 (26.82%)
Negative Rainfall Shock (>20% less than median)	4,010 (39.12%)	23 (1.98%)	327 (10.17%)	2,650 (73.18%)
Number of Observations	**10,250**	**1,164**	**3,216**	**3,621**

Table 4: Means & P-values from Tests of Mean Differences on Dependent Variables

	Full Sample	***No Rainfall Shock***	***Negative Rainfall Shock***	***Difference***	***P-value***
Plot-Level					
Maize Yields	1441.259	1636.098	1085.003	551.095	0.000
Number of Observations	**11,354**				
Value of Agricultural Output	52183.3	55623.61	44370.2	11253.41	0.000
Number of Observations	**15,381**	**10,947 (71.17%)**	**4,434 (28.83%)**		
	Full Sample	***No Rainfall Shock***	***Negative Rainfall Shock***	***Difference***	***P-value***
Household-Level					
Per Capita Consumption Expenditures	46817.19	47838.63	44748	3090.64	.076
Per Capita Expenditures on Food	29545.54	30374.44	27866.39	2508.052	.008
Per Capita Expenditures on Non-Food Items	17802.1	18028.7	17343.06	685.6325	.468
Shannon Index	1.263	1.278	1.231	0.047	0.073
Number of Observations	**9,473**	**6,434 (67.92%)**	**3,039 (32.08%)**		

Note: Consumption expenditures are in Malawian Kwacha (MK)
The tentative poverty line is 40,412 MK leaving approximately 43% of our sample in poverty

Table 5. Summary Statistics for Value of Output

	Full Sample		*No Rainfall Shock*		*Negative Rainfall Shock*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Inter_crop	.389	.488	.275	.446	.679	.467
Local Maize	.397	.489	.366	.481	.476	.499
Hybrid Maize	.326	.469	.310	.463	.365	.481
Tobacco	.076	.266	.095	.293	.031	.172
Groundnut	.089	.285	.111	.314	.036	.186
Plot Area	.386	.338	.389	.350	.378	.305
% Agricultural land (within 2 km)	49.54	25.02	47.41	24.93	54.89	24.42
Elevation (m)	891.21	328.81	946.65	323.66	751.72	299.00
Irrigation	.004	.062	.003	.056	.006	.074
Distance from Plot to Household (km)	2.15	11.04	2.24	12.39	1.93	6.48
Soil Index	.036	2.15	.007	2.18	.108	2.05
Owned	.9	.299	.888	.134	.931	.254
Fallow Years	.071	.999	.072	1.14	.067	.500
Organic Fertilizer	.112	.316	.112	.315	.113	.317
Inorganic Fertilizer	165.64	305.98	167.76	333.00	160.32	223.96
Herbicides/Pesticides	1.44	13.32	1.49	14.31	1.33	10.44
Family Female Labor Input	1616.36	5438.47	1604.94	5431.72	1645.08	5455.89
Family Male Labor Input	1366.55	3720.76	1413.41	3775.09	1248.67	3578.09
Family Children Labor Input	241.73	1887.95	248.96	2091.04	223.56	1237.49
Hired Labor Input	8.91	41.04	9.47	33.95	7.51	54.95
Exchange Labor Input	3.81	22.96	4.21	26.013	2.80	12.24
Age of Manager	42.94	15.82	43.00	15.64	42.79	16.28
Manager Years of Schooling	5.28	3.95	5.42	3.98	4.94	3.85
Manager – Chronic Disease	.09	.29	.089	.284	.095	.293
Manager of plot and enterprise	.15	.36	.152	.359	.153	.360
Wage and Ganyu income of manager	.24	.43	.233	.423	.263	.440
Number of yrs manager at current residence	33.28	19.46	33.12	19.35	33.67	19.74
Father of manager – primary and above	.12	.33	.124	.33	.112	.316
Female Manager	.27	.44	.249	.433	.305	.460
Children (0-5)	.99	.94	1.12	.944	.939	.910
Children (6-14)	1.38	1.29	1.42	1.31	1.29	1.24
Male Adults (15-59)	1.12	.87	1.158	.89	1.02	.81
Female Adults (15-59)	1.18	.74	1.20	.76	1.13	.68
Maximum Years of Schooling in Household	7.26	3.42	7.41	3.43	6.9	3.38
Agricultural Extension Services Received	.306	.461	.329	.47	.249	.432
Wealth Index	-.509	2.27	-.443	2.366	-.677	2.00

Table 5 (cont.)

Agricultural Index	.691	1.385	.79	1.41	.445	1.28
Household distance to main road	9.56	10.31	8.82	10.10	11.41	10.57
Household distance to nearest locality with (20000+)	38.63	20.93	39.37	21.5	36.41	19.25
Household distance to market	8.13	5.48	8.23	5.64	7.89	5.04
Northern Region	.177	.382	.224	.417	.059	.235
Central Region	.399	.49	.517	.49	.101	.301
Rural	.94	.237	.935	.246	.952	.213
Number of Observations	**16,366**		**11,711**		**4,655**	

Table 6. Summary Statistics for Welfare

	Full Sample		*No Rainfall Shock*		*Negative Rainfall Shock*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household Composition						
Children (0-5)	.965	.932	.997	.948	.898	.896
Children (6-14)	1.31	1.26	1.34	1.28	1.24	1.22
Male Adults (15-39)	.804	.747	.828	.759	.754	.717
Female Adults (15-39)	.875	.662	.892	.674	.838	.635
Male Adults (40-59)	.241	.43	.252	.437	.216	.413
Female Adults (40-59)	.246	.435	.249	.436	.241	.413
Household Head Characteristics						
Gender (1=female)	.252	.434	.238	.426	.282	.449
Age	43.18	16.53	43.2	16.39	43.11	16.82
Number of Years lived in present residence	32.83	24.86	33.11	25.13	32.23	35.28
Ethnicity						
Chewa	.53	.499	.537	.499	.515	.499
Tumbuka	.104	.305	.133	.339	.042	.20
Yao	.096	.295	.115	.319	.056	.229
Religion						
Christianity	.826	.379	.798	.402	.886	.318
Islam	.117	.321	.140	.347	.068	.253
Mother's Education						
Primary	.064	.246	.069	.254	.055	.228
Junior Primary	.022	.148	.025	.155	.018	.133
MSCE and above	.016	.126	.023	.148	.022	.147
Household Characteristics						
Highest Level of Schooling in Household	6.79	3.47	6.93	3.46	6.48	3.47
Distance to Market	8.51	5.78	8.78	6.12	7.93	5.00
Distance to Road	10.06	10.67	9.54	10.83	11.16	10.26
Cultivated Land	1.50	28.44	1.89	34.47	.685	1.81
Wealth Index	-.888	1.76	-.840	1.82	-.992	1.64
Community Characteristics						
Clinic	.225	.418	.250	.433	.173	.378

Table 6 (cont.)

Village Clinic	.287	.418	.319	.466	.219	.414
Tarred Road	.159	.366	.189	.391	.095	.293
Cost of Transportation to Urban Location	804.81	541.53	855.7	569.56	697.07	458.60
Bed Net Support	.523	.499	.554	.497	.458	.498
Number of Observations	**9,473**		**6,434**		**3,039**	

Table 7. Regression Results – Value of Output

Variable	Maize Yields	Value of Agricultural Output
Negative Rainfall Shock	-0.210***	-0.176***
	(0.044)	(0.040)
Plot Characteristics		
Plot Area (log)	-0.404***	-0.341***
	(0.035)	(0.030)
Plot Area Squared (log)	0.032***	0.042***
	(0.012)	(0.009)
Distance from Plot to Household (km)	-0.000	-0.001*
	(0.001)	(0.001)
Mixed crop stand on the plot (inter-cropped)		0.124***
		(0.029)
Inputs		
Inorganic Fertilizer (log)	0.096***	0.084***
	(0.005)	(0.005)
Pesticides (dummy)	0.113	0.331***
	(0.116)	(0.078)
Family Manager Labor Input (Hrs/Ha)	0.071***	0.074***
	(0.021)	(0.018)
Family Manager Labor Input Squared	-0.010***	-0.010***
	(0.003)	(0.002)
Family Female Labor Input (Hrs/Ha)	0.016**	0.010*
	(0.007)	(0.006)
Family Male Labor Input (Hrs/Ha)	0.016***	0.018***
	(0.006)	(0.005)
Family Children Labor Input (Hrs/Ha)	0.008*	0.006
	(0.005)	(0.004)
Hired Labor Input (Hrs/Ha)	0.065***	0.076***
	(0.009)	(0.008)
Exchange Labor Input (Hrs/Ha)	0.032***	0.026**
	(0.012)	(0.012)
Manager Characteristics		
Age of Manager	0.000	-0.001
	(0.001)	(0.001)
Number of Years of Schooling	0.006*	0.003
	(0.003)	(0.003)
Female Manager	-0.100***	-0.076***
	(0.031	(0.025)

Table 7 (cont.)		
Household Human Capital		
Household Size	0.007	0.012**
	(0.006)	(0.005)
Household Dependency Ratio	-0.001	0.003
	(0.011)	(0.010)
Agricultural Extension Services Received	0.056**	0.042**
	(0.023)	(0.021)
Household Physical Capital		
Non-farm Income	-0.050**	-0.063***
	(0.020)	(0.017)
Other Income	-0.029	-0.009
	(0.031)	(0.028)
Wealth Index	0.076***	0.066***
	(0.007)	(0.006)
Index on Agricultural implements and machinery access	0.037***	0.034***
	(0.010)	(0.008)
Crop type on plot		
(Local Maize - Omitted Category)		
Hybrid Maize		0.074***
		(0.020)
Tobacco		1.120***
		(0.039)
Groundnut		0.041
		(0.041)
Other Crops		0.069
		(0.063)
Region		
Agroecological Zone = Tropic-warm/semiarid	0.137**	0.037
	(0.069)	(0.070)
Agroecological Zone = Tropic-warm/subhumid	0.190**	0.184**
	(0.076)	(0.076)
Agroecological Zone = Tropic-cool/semiarid	0.143*	0.015
	(0.077)	(0.076)
Agroecological Zone = Tropic-warm/semiarid (Omitted Category)		

Table 7 (cont.)		
District Fixed Effects		
Karonga	-0.385***	-0.017
	(0.104)	(0.110)
Nkhatabay	-0.341***	-0.216***
	(0.074)	(0.070)
Rumphi	-0.225***	0.050
	(0.074)	(0.061)
Mzimba	-0.223***	-0.182***
	(0.069)	(0.064)
Kasungu	0.036	0.007
	(0.064)	(0.058)
Nkhita kota	-0.374***	0.055
	(0.092)	(0.083)
Lilongwe	-0.044	-0.111
	(0.068)	(0.069)
Mchinji	0.111	0.001
	(0.075)	(0.061)
Dedza	-0.246***	-0.103
	(0.073)	(0.089)
Ntcheu	-0.180**	-0.059
	(0.070)	(0.073)
Mangochi	-0.119	-0.051
	(0.075)	(0.068)
Machinga	-0.383***	-0.069
	(0.091)	(0.092)
Zomba	-0.671***	-0.317***
	(0.094)	(0.075)
Chiradzulu	-0.648***	-0.253***
	(0.110)	(0.098)
Blanytyre	-0.852***	-0.311***
	(0.103)	(0.075)
Mwanza	-0.869***	-0.183*
	(0.113)	(0.095)
Thyolo	-0.627***	-0.267***
	(0.111)	(0.095)
Mulanje	-0.992***	-0.694***
	(0.111)	(0.100)
Phalombe	-0.860***	-0.520***
	(0.100)	(0.098)
Chikwawa	-0.805***	-0.496***
	(0.154)	(0.140)
Nsanje	-0.734***	-0.398***
	(0.123)	(0.117)
Balaka	-0.450***	-0.172**
	(0.088)	(0.075)
Neno	-0.588***	-0.182**
	(0.115)	(0.087)
_constant	6.005***	9.273***
	(0.096)	(0.088)
Number of Observations	**11,354**	**15,337**
Adjusted R-squared	**0.37**	**0.36**

Robust standard errors in parentheses, clustered by enumeration area
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness Check

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Negative Rainfall Shock	-0.314***	-0.224***	-0.209***	-0.189***	-0.18***
	(0.04)	(0.045)	(0.044)	(0.042)	(0.039)
Number of Observations	**15,381**	**15,381**	**15,381**	**15,337**	**15,337**
Adjusted R-squared	**0.021**	**0.062**	**0.147**	**0.245**	**0.36**

(1) Negative Rainfall Shock
(2) Add District Fixed Effects
(3) Add Inputs
(4) Add Primary Crop Planted
(5) Full Model

Table 9: Welfare Regression Results

Variable	Total Consumption	Food Consumption	Non-Food Consumption	Shannon Index
Negative Rainfall Shock	-0.044*	-0.054**	-0.027	-0.070***
	(0.025)	(0.027)	(0.028)	(0.026)
Household Composition				
Household Size	-0.110***	-0.112***	-0.111***	-0.022***
	(0.005)	(0.005)	(0.006)	(0.005)
% Children (0-5)	-0.008***	-0.007***	-0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
% Children (6-14)	-0.007***	-0.006***	-0.008***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
% Male Adults	-0.003***	-0.002***	-0.003***	-0.000
(15-39)	(0.001)	(0.001)	(0.001)	(0.001)
% Female Adults	-0.002***	-0.001	-0.003***	0.001
(15-39)	(0.001)	(0.001)	(0.001)	(0.001)
% Male Adults	0.001	0.000	0.001	0.000
(40-59)	(0.001)	(0.001)	(0.001)	(0.001)
% Female Adults	-0.000	0.000	-0.001	0.001
(40-59)	(0.001)	(0.001)	(0.001)	(0.001)
Household Head Characteristics				
Gender (1=female)	-0.039**	-0.039**	-0.030	-0.087***
	(0.016)	(0.019)	(0.019)	(0.018)
Age	-0.005***	-0.004***	-0.007***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Highest Level of Schooling in Household	0.011***	0.007***	0.019***	0.013***
	(0.002)	(0.003)	(0.003)	(0.002)
Father's Education				
Primary	0.137***	0.141***	0.141***	0.087***
	(0.027)	(0.030)	(0.031)	(0.030)
Junior Primary	0.151***	0.122**	0.195***	0.122***
	(0.048)	(0.053)	(0.059)	(0.041)
MSCE and above	0.181***	0.184***	0.149***	0.104***
	(0.041)	(0.046)	(0.052)	(0.040)
Household Assets				
Wealth Quintile 1 (Omitted Category)				
Wealth Quintile 2	0.120***	0.101***	0.171***	0.086***
	(0.017)	(0.020)	(0.020)	(0.018)
Wealth Quintile 3	0.296***	0.233***	0.421***	0.203***
	(0.018)	(0.021)	(0.023)	(0.020)

Table 9 (cont.)

Wealth Quintile 4	0.480***	0.367***	0.716***	0.308***
	(0.020)	(0.022)	(0.025)	(0.023)
Wealth Quintile 5	0.907***	0.705***	1.274***	0.523***
	(0.027)	(0.029)	(0.034)	(0.028)
Household Income				
Non-farm Income	0.084***	0.077***	0.111***	0.081***
	(0.014)	(0.016)	(0.016)	(0.014)
Other Income	0.062***	0.057***	0.079***	0.065***
	(0.017)	(0.020)	(0.021)	(0.017)
Borrowed Cash or Inputs	0.076***	0.053**	0.126***	0.053***
	(0.020)	(0.022)	(0.023)	(0.020)
Household Location				
Distance to City	-0.001**	-0.000	-0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to Main Road	-0.002	-0.002	-0.002	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
Community has bank/microfinance institution	0.014	0.001	0.045	0.001
	(0.030)	(0.035)	(0.033)	(0.036)
Community has agricultural extension officer	0.103***	0.113***	0.085***	0.078***
	(0.024)	(0.025)	(0.028)	(0.022)
Karonga	-0.023	0.048	-0.155*	0.215***
	(0.064)	(0.066)	(0.081)	(0.056)
Nkhatabay	0.095	0.175***	-0.002	0.508***
	(0.070)	(0.068)	(0.083)	(0.055)
Rumphi	0.240***	0.269***	0.188**	0.341***
	(0.074)	(0.075)	(0.082)	(0.064)
Mzimba	0.057	0.117*	-0.056	0.090
	(0.068)	(0.067)	(0.076)	(0.055)
Kasungu	0.387***	0.334***	0.480***	0.071
	(0.061)	(0.062)	(0.069)	(0.055)
Nkhota kota	0.422***	0.417***	0.446***	0.278***
	(0.058)	(0.059)	(0.066)	(0.057)
Ntchisi	0.429***	0.434***	0.406***	0.022
	(0.068)	(0.072)	(0.077)	(0.066)
Dowa	0.263***	0.184**	0.380***	-0.066
	(0.064)	(0.072)	(0.067)	(0.066)
Salima	0.268***	0.300***	0.236***	0.195***
	(0.065)	(0.062)	(0.086)	(0.053)
Mchinji	0.109*	0.030	0.218***	-0.088
	(0.063)	(0.070)	(0.067)	(0.068)

Table 9 (cont.)				
Dedza	0.236***	0.234***	0.242***	0.237***
	(0.055)	(0.058)	(0.076)	(0.049)
Ntcheu	0.236***	0.207***	0.311***	0.096*
	(0.058)	(0.061)	(0.063)	(0.049)
Mangochi	0.011	0.051	-0.070	0.085
	(0.059)	(0.062)	(0.062)	(0.057)
Machinga	0.032	0.075	-0.043	0.184***
	(0.070)	(0.073)	(0.072)	(0.064)
Zomba	0.102	0.042	0.212***	0.258***
	(0.067)	(0.074)	(0.071)	(0.071)
Chiradzulu	0.257***	0.179***	0.373***	0.263***
	(0.060)	(0.063)	(0.070)	(0.060)
Blanytyre	0.283***	0.216***	0.413***	0.208***
	(0.060)	(0.061)	(0.067)	(0.056)
Mwanza	0.047	0.112*	-0.084	0.047
	(0.054)	(0.059)	(0.060)	(0.069)
Thyolo	0.277***	0.330***	0.191***	0.338***
	(0.050)	(0.052)	(0.062)	(0.050)
Mulanje	0.064	-0.033	0.223***	0.105*
	(0.070)	(0.077)	(0.071)	(0.062)
Phalombe	0.103	0.033	0.248***	0.160**
	(0.073)	(0.082)	(0.071)	(0.071)
Chikwawa	-0.193***	-0.155**	-0.285***	-0.041
	(0.067)	(0.075)	(0.077)	(0.068)
Nsanje	-0.302***	-0.248***	-0.420***	-0.074
	(0.075)	(0.086)	(0.073)	(0.080)
Balaka	-0.003	-0.042	0.083	-0.014
	(0.061)	(0.064)	(0.064)	(0.069)
Neno	0.059	0.104	-0.031	0.010
	(0.071)	(0.075)	(0.074)	(0.076)
_constant	11.165***	10.672***	10.093***	1.166***
	(0.081)	(0.092)	(0.090)	(0.079)
Number of Observations	**8,399**	**8,399**	**8,399**	**8,399**
Adjusted R-squared	**0.487**	**0.374**	**0.511**	**0.241**

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Heterogeneity of Impact across Types of Primary Crops on Plots

Variable	Negative Rainfall Shock	Number of Observations	R2a
Crop type on plot			
Local Maize	-0.214***	6110	.32
	(0.041)		
Hybrid Maize	-0.163***	4836	.29
	(0.052)		
Tobacco	-0.069*	1229	.23
	(0.079)		
Groundnut	-0.411***	1412	.22
	(0.096)		

Robust standard errors in parentheses, clustered by enumeration area
*** p<0.01, ** p<0.05, * p<0.1
Other independent variables included are those used in Table 7.

Table 11. Heterogeneity of Impact across Agroecological Zones

Variable	Negative Rainfall Shock	Number of Observations	R2a
Region			
Agroecological Zone = Tropic-warm/semiarid	-0.347*** (0.027)	7141	.269
Agroecological Zone = Tropic-warm/subhumid	-0.421*** (0.028)	5132	.276
Agroecological Zone = Tropic-cool/semiarid	-0.092* (0.05)	1926	.287
Agroecological Zone = Tropic-warm/semiarid	-0.489 (0.093)	1182	.268

Robust standard errors in parentheses, clustered by enumeration area
*** p<0.01, ** p<0.05, * p<0.1
Other independent variables included are those used in Table 7.

Table 12: Heterogeneity of Impact across Household Characteristics

Variable	Total Consumption	Shannon Index	Total Consumption	Shannon Index	Total Consumption	Shannon Index
Negative Rainfall Shock	-0.095***	-0.094***	-0.097***	-0.095***	0.014***	0.015***
	(0.016)	(0.016)	(0.013)	(0.013)	(0.002)	(0.002)
Nonfarm Income	0.084***	0.070***			0.000	0.002
	(0.013)	(0.025)			(0.003)	(0.004)
Shock*Nonfarm Income	-0.037	-0.000				
	(0.023)	(0.024)				
Access to Credit			0.145***	0.040**		
			(0.019)	(0.020)		
Shock*Access to Credit			-0.123***	0.009		
			(0.037)	(0.038)		
Highest Level of Education					0.014***	0.015***
					(0.002)	(0.002)
Shock*Education					0.000	0.002
					(0.003)	(0.004)
Number of Observations	**8,399**	**8,399**	**8,399**	**8,399**	**8,399**	**8,399**
Adjusted R-squared	**.428**	**.197**	**.43**	**.195**	**.428**	**.198**

Robust standard errors in parentheses, clustered by enumeration area
*** p<0.01, ** p<0.05, * p<0.1
Other independent variables included are those used in Table 8.

Appendix A

Table A.1. Results for All Thresholds

Variable	**Maize Yields**	**R2a**	**Value of Agricultural Output**	**R2a**
>1 Standard Deviations below mean	-0.103* (0.054)	0.362	-0.117** (0.048)	0.361
>10% below mean	-0.165*** (0.037)	0.366	-0.142*** (0.033)	0.363
>15% below mean	-0.221*** (0.039)	0.368	-0.185*** (0.036)	0.364
>20% below mean	-0.122*** (0.047)	0.363	-0.137*** (0.042)	0.362
>25% below mean	-0.128* (0.067)	0.362	-0.16** (0.063)	0.361
>30% below mean	-0.153* (0.088)	0.362	-0.214** (0.083)	0.361
>10% below median	-0.185*** (0.038)	0.366	-0.146*** (0.033)	0.362
>15% below median	-0.231*** (0.042)	0.369	-0.191*** (0.038)	0.364
>20% below median	-0.21*** (0.044)	0.367	-0.18*** (0.04)	0.363
>25% below median	-0.246*** (0.051)	0.367	-0.244*** (0.048)	0.365
>30% below median	-0.078 (0.091)	0.361	-0.16** (0.069)	0.361
Number of Observations	**11,354**		**15,381**	